A RAND NOTE

Predicting Enlistment for Recruiting Market Segments

Bruce R. Orvis, Martin T. Gahart,
James R. Hosek

September 1989

RAND

REPRODUCED FROM
BEST AVAILABLE COPY

Unclassified

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

REPORT DOCUMENTATION PAGE		READ INSTRUCTIONS BEFORE COMPLETING FORM
1. REPORT NUMBER N-2852-FMP	2. GOVT ACCESSION NO.	3. RECIPIENT'S CATALOG NUMBER
4. TITLE (and Subtitle) Predicting Enlistment for Recruiting Market Segments		5. TYPE OF REPORT & PERIOD COVERED interim
		6. PERFORMING ORG. REPORT NUMBER
7. AUTHOR(s) Bruce R. Orvis, Martin T. Gahart, James R. Hosek		8. CONTRACT OR GRANT NUMBER(s) MDA903-85-C-0030
9. PERFORMING ORGANIZATION NAME AND ADDRESS The RAND Corporation 1700 Main Street Santa Monica, CA 90406		10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS
11. CONTROLLING OFFICE NAME AND ADDRESS Office, Assistant Secretary of Defense for Force Management and Personnel Washington, DC 20301-4000		12. REPORT DATE September 1989
		13. NUMBER OF PAGES 37
14. MONITORING AGENCY NAME & ADDRESS(if different from Controlling Office)		15. SECURITY CLASS. (of this report) unclassified
		15a. DECLASSIFICATION/DOWNGRADING SCHEDULE

16. DISTRIBUTION STATEMENT (of this Report)

Approved for Public Release; Distribution Unlimited

17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)

No Restrictions

18. SUPPLEMENTARY NOTES

19. KEY WORDS (Continue on reverse side if necessary and identify by block number)

Recruiting
Forecasting
Models
Decision Making
Demography
Enlisted Personnel

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

see reverse side

DD FORM 1 JAN 73 1473

Unclassified

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

A RAND NOTE

N-2852-FMP

Predicting Enlistment for Recruiting Market Segments

Bruce R. Orvis, Martin T. Gahart,
James R. Hosek

September 1989

Prepared for
The Assistant Secretary of Defense
(Force Management and Personnel)

RAND

This Note examines the relationship between geodemographic information and individual (micro) models of enlistment decisionmaking. Although geodemographic systems can identify groups with varying enlistment rates, they provide limited information on the factors underlying enlistment. Given the apparent advantages of the micro models, the authors undertook to determine whether (1) differences in enlistment rates among the geodemographic groups are attributable to the types of factors included in the micro models; (2) including geodemographic information in the individual-level models improves the prediction of enlistment decisionmaking; and (3) the factors predicting enlistment vary by geodemographic group. Because geodemographic groupings distinguish areas with different enlistment rates, they could be used in efforts such as targeting the mailing of recruiting literature and allocating recruiters or recruiting goals. At the same time, the authors found that enlistment decisionmaking micro models capture much of the same information. Finally, the research shows that the micro models are superior to the geodemographic information in predicting individuals' enlistment decisions and that the inclusion of geodemographic information in the micro models has little meaningful impact on enlistment behavior predictions. (SDW)

PREFACE

The research reported in this Note is part of RAND's Segmentation Analysis of Market Survey Information and Enlistment Behavior. The project seeks to synthesize and, where appropriate, extend the findings of recent work concerned with segmenting the military recruiting market. The Note examines the question of whether geodemographic clusters add information concerning the recruiting potential of market segments to that available through existing models of individual enlistment decisionmaking. The work was originally briefed to the sponsor in the summer of 1986. A second element of the project pertains to the modeling of factors leading to application for military service and to enlistment among military applicants; it will be covered in a separate RAND report.

The study was sponsored by the Assistant Secretary of Defense (Force Management and Personnel) and was carried out by the Defense Manpower Research Center in the National Defense Research Institute, RAND's OSD-supported federally funded research and development center.

SUMMARY

This study was undertaken in the context of prior research results concerning enlistment behavior in various segments of the recruiting market. Research with *aggregate* data had demonstrated that markets with different enlistment rates could be identified by segmenting the recruiting market geodemographically, that is, according to the geographic and demographic characteristics of particular localities. Research concerning *individual* enlistment decisionmaking, based on data from the YATS (Youth Attitude Tracking Study) and the NLS (National Longitudinal Study of Youth Labor Market Experience), had identified specific enlistment predictor variables and shown that the relationship between enlistment and specific attributes differs for different market segments, such as high school students versus youths no longer in high school.

This Note examines the relationship between ACORN (A Clustering of Residential Neighborhoods, i.e., geodemographic) information and individual-level (micro) models of enlistment decisionmaking. Although geodemographic systems identify groups with varying enlistment rates, they provide limited information on the factors underlying enlistment. Moreover, enlistment rate projections based on geodemographic clusters are relatively static, because major reassessments of the geodemographic composition of the U.S. population are undertaken infrequently. In contrast, the YATS and NLS models of individual enlistment decisionmaking rely on relationships that are well understood and, for the YATS, on information that is updated frequently. Given these apparent advantages of the micro models, our task was to determine whether: (a) the differences in enlistment rates among the geodemographic groups are attributable to the types of factors included in the micro models; (b) including ACORN information in the individual-level models improves the prediction of enlistment decisionmaking; and (c) the factors predicting enlistment vary by geodemographic group, that is, different models are required for different geodemographic groups.

PRECEDING PAGE BLANK

We used several databases to address these issues. The first consists of responses from the YATS and matched records from the MEPS (Military Entrance Processing Station) Reporting System (MRS) for those respondents who took the written test to qualify for military service and possibly enlisted. A second database consists of information from the 1979 AFEES (Armed Forces Entrance and Examining Station) and NLS Surveys. The third consists of ACORN cluster information concerning the distribution of the U.S. youth population.

Given our plan to compare geodemographic and micro model information--which typically included county of residence but not ZIP code--the first step was to examine the similarity between ZIP code- and county-based (Federal Information Processing Standards--FIPS) estimates of enlistment interest for the ACORN clusters. (Up to this time, the ACORN-enlistment relationship had been validated only for ZIP code-based ACORN profiles.) This effort was undertaken for a subset of the YATS survey waves containing both FIPS and ZIP code information. The measures of enlistment interest for each cluster were the positive propensity rate (the proportion of individuals stating that they are likely to enlist), the production written examination rate (the proportion of persons testing at MEPS or official remote sites to qualify for military service), and the actual enlistment rate.

Our analyses showed that the FIPS and ZIP approaches produce similar results, thus validating the FIPS approach. There were high Pearson product-moment and rank order correlations between the rates estimated using the two approaches for each measure of enlistment interest, ranging from .64 to .80. The analysis showed that the difference in rate estimates produced by the two approaches is small both in absolute terms and as compared with the means and standard deviations of the estimates. This result is especially true for large (populous) ACORNs, which contain more than 75 percent of the population.

We next moved to the primary topic: the relationship between the information contained in geodemographic databases such as the ACORN and that contained in individual-level models of enlistment decisionmaking. We began by using the micro models to predict enlistment rates for the

ACORN clusters and compare the predicted rates with the clusters' observed enlistment rates. In a second analysis, we added ACORN information to the vector of variables in each micro model to assess the extent to which it improved the prediction of enlistment. Conceptually, this analysis is related to the one described above, because, to the extent the relevant geodemographic information is captured by the micro models, adding the ACORN profiles should have little effect.

We found that the existing micro models explain most of the variation in enlistment rates among the ACORN clusters; correlations between the enlistment rates predicted for the clusters by the micro models and their actual enlistment rates were .73 to .84. Second, and relatedly, we found that information from the ACORN database does little to improve the prediction of enlistment in the micro models. Several aspects of the analysis support this conclusion. For one, few ACORN groups or clusters are statistically significant in predicting enlistment, controlling for the factors in the micro models. Moreover, for the few ACORN groups that are significant, there is little evidence of interaction with other variables. This finding implies that the micro models can be used to predict enlistment rates among different geodemographic groups. Finally, adding ACORN information to the micro models has virtually no impact on the distribution of predicted enlistment probabilities.

In short, the results are consistent with the notion that geodemographic groupings provide information useful in distinguishing areas with different enlistment rates, and, thus, that they could be used in efforts such as targeting the mailing of recruiting literature, and allocating recruiters or recruiting goals. At the same time, the research suggests that enlistment decisionmaking micro models--such as those based on the YATS-MRS and AFEES-NLS databases--capture much of the same information. These models could be used to predict local enlistment rates and provide similar guidance. They also could be used in developing profiles of likely enlistees. Moreover, the general absence of significant interactions between the ACORN and micro model variables suggests that differences in enlistment rates among geodemographic groups can be attributed to their differences on the

variables in the micro models, not to differences in the enlistment decisionmaking process. Finally, the work shows that the micro models are superior to the geodemographic information in predicting individuals' enlistment decisions and that the inclusion of geodemographic information in the micro models has little meaningful impact on predicted enlistment behavior.

ACKNOWLEDGMENTS

This study was made possible by the support of W. S. Sellman, Director of Accession Policy, and Zahava Doering, then Chief, Survey and Market Analysis Division, Defense Manpower Data Center (DMDC). We are also grateful to J. J. Miller, formerly of DMDC, who worked with us at various stages of this project, and to Paul Nickens, Robert Brandewie, and their staffs, all of DMDC, who provided the primary databases used in the research.

At RAND, we are grateful to our colleagues Richard Buddin, for his advice and support, and Sheila Kirby, for her helpful review of this manuscript. Finally, credit must go to Alvin Ludwig, Marilyn Yokota, and Kerrie Avery for their help in preparing this Note.

CONTENTS

PRECEDING PAGE BLANK

TABLES

I. INTRODUCTION

This Note synthesizes two lines of prior research and assesses their usefulness. Specifically, it examines the relationship between:

1. Aggregate-level information that identifies geodemographic groups with different enlistment rates
2. Individual-level (micro) models of enlistment which identify enlistment predictor variables (characteristics that distinguish individuals with different probabilities of enlistment).

The results will help to develop models for forecasting enlistment rates in different generic markets or localities (each composed of various proportions of youth in those generic markets). Information about the recruiting potential of a locality can be useful in guiding the allocation of recruiting and advertising resources.

SUMMARY OF PRIOR RESEARCH RESULTS

The goal of the segmentation project is to synthesize and, where appropriate, extend the results of several lines of recent work that identify segments of the military recruiting market. First, *aggregate*-level research has demonstrated that differences in enlistment rates among geographical areas can be modeled using the demographic characteristics of the areas; this implies that the recruiting market can be segmented geodemographically. In particular, it was known that enlistment rates varied significantly with ACORN (A Clustering of Residential Neighborhoods) clusters, which categorize and group geographical areas according to factors such as income level, ethnic mix, and type of housing, e.g., "newer high value suburbs, upper income" (see CACI, 1986). Marketing categorizations of neighborhoods or subpopulations, such as the ACORN system, assume that the residents of an area or members of a subpopulation share important values and behave

the same way in the marketplace because they have similar characteristics and life styles. The full set of ACORN clusters is shown in the Appendix.

Second, previous research concerning *individual* enlistment decisionmaking with the YATS (Youth Attitude Tracking Study) and the NLS (National Longitudinal Study of Youth Labor Market Experience) has shown that the recruiting market can be segmented according to the characteristics of individuals; the relationship between enlistment and specific attributes differs for such market segments. In particular, factors differ in importance for high school students as compared with youths no longer in high school and for youths expecting further education in comparison with those not expecting additional education (Orvis and Gahart, 1985; Hosek and Peterson, 1985; Hosek, Peterson, and Eden, 1986).

Third, research on the relationship between stated enlistment intentions and actual enlistment actions shows that one's probability of enlisting varies significantly with the strength of one's stated intention to enlist. At the same time, the work found that, because it represents most individuals, the negative intention group--that is, persons stating that they will probably not enlist--constitutes an important source of enlistees (Orvis and Gahart, 1985) and differs in background characteristics from persons with positive intentions.

Finally, prior research with military applicants--people with enough interest in the military to take the AFQT (Armed Forces Qualification Test) to qualify for military service--has shown that they enlist at a much higher rate than the national youth population, but, still, that about one-half of them do not enlist (Berryman, Bell, and Lisowski, 1983).

SUGGESTED RESEARCH DIRECTIONS

The early work suggested a number of promising avenues related to market segmentation, which, together, formed the basis for this project. The finding that enlistment rates vary significantly among ACORN clusters suggests that the clustering scheme might be useful in recruiting efforts and raises questions about the relationship between

geodemographic factors and the factors identified in individual-level (micro) models of enlistment decisionmaking; such questions include whether different micro models may be required for different ACORN clusters. The finding that the negative intention group constitutes an important source of enlistees--approximately 70 percent of the male youth population falls into this group--raises questions concerning whether segmenting the market into groups with positive and negative intentions is important. Do the different characteristics of the persons with positive and negative intentions imply that different enlistment decisionmaking factors are important for the two groups, or does the difference in characteristics primarily distinguish the enlistment plans (i.e., intentions) of the two groups? Finally, the military applicant population is an important pool of potential enlistees, because it consists of individuals who have actively expressed a potential interest in military service and who are known to recruiters. They have seen a recruiter, scheduled the written test to qualify for military service, and have reported to complete the test. Because their enlistment rate is higher and because, despite this, approximately one-half of the applicants ultimately do not enlist, additional applicant research should prove fruitful. That research should try: (1) to identify factors that could promote enlistment among these potential recruits and (2) to determine whether such factors differ from those promoting application in the general youth population.

CURRENT STUDY

The research reported here integrates earlier studies on ACORN information and micro models of enlistment decisionmaking; the ACORN findings serve as the point of departure. Work on the other issues--such as the factors motivating enlistment among applicants--will be reported later. Because enlistment rates vary for different geodemographic groups, the ACORN system appeared potentially useful in predicting enlistment rates for different markets/localities and in targeting resources. However, we were concerned that ACORN's usefulness might be limited for two reasons: First, although the system identifies groups with varying enlistment rates, it provides little information on

the factors underlying enlistment in the groups, which can be similar or different. Second, the enlistment rate projections based on geodemographic clusters are static because the clusters rely on estimated population characteristics which are revised only periodically, when a major reassessment of the geodemographic composition of the U.S. population is undertaken.

In contrast, the models of individual enlistment decisionmaking noted earlier rely on relationships that are well understood and, for the YATS, on information that is updated frequently. Thus, our task was to determine the relationship between the ACORN or geodemographic enlistment rate differences and the factors identified in the YATS and AFEES-NLS micro models. Specifically, we sought to answer three questions:

1. *Do the individual-level models explain the enlistment rate differences among the geodemographic groups?* In other words, are the differences we find in enlistment rates among the geodemographic groups attributable to the types of factors included in the models of individual enlistment decisionmaking, or do databases such as the ACORN contain important unique information, such as context or "cultural" effects?[1]
2. Relatedly, *does including ACORN information in the micro models improve the prediction of individual enlistment decisionmaking?*
3. *Do the factors predicting enlistment vary by geodemographic group* to an appreciable extent? It is important to know whether given enlistment models--such as the YATS and AFEES-NLS micro models--can be used for different geodemographic groups, or whether different enlistment models must be constructed.

---

[1]The question here is whether neighborhood or cultural values have an effect on military enlistment that is independent of the individual demographic characteristics identified in the micro models.

DATABASES

We used several databases to address these issues. The first consists of matched results from the YATS and the MEPS (Military Entrance Processing Station) Reporting System (MRS) records of enlistment and testing actions. The database provides enlistment and testing records through March 1985 for 36,648 young male respondents to the 1976 through 1981 YATS surveys. The MRS information thus reflects the long-term (at least 42 months after the YATS survey) enlistment and testing actions taken by high school students and youths not in high school.

A second database used in our research consists of information from the 1979 AFEES (Armed Forces Entrance and Examining Station) and NLS Surveys. This database differs from the YATS-MRS database in important ways. First, the database was constructed to include (male) high school seniors and nonstudent recent high school graduates, the prime recruiting population. The YATS sample also includes student graduates, persons in earlier years of high school, and high school dropouts. Second, the AFEES-NLS database is a choice-based sample. That is, it was designed to analyze enlistment decisions among male youths, aged 17 to 22, at a point in time, spring 1979. Inferences about the determinants of enlistment are made by statistically contrasting the characteristics of the 4443 enlistees (AFEES) with those of the 1093 nonenlistees (NLS). (See Hosek and Peterson, 1985, for a full discussion.) By comparison, the YATS database follows the same individuals over time--it is a longitudinal file--to ascertain their enlistment behavior and its relationship to individual characteristics. Both approaches have proved informative, and indeed many of their inferences are similar.

The third major database consists of ACORN (geodemographic) information on the distribution of the U.S. youth population. There are two versions of the database. The first reflects the percentage of the male youth population in each of the 44 ACORN clusters for each ZIP code in the United States. The second reflects the percentage of the youth population falling into each of the 44 ACORN clusters for each county

(Federal Information Processing Standards--FIPS--code) in the United States. The Defense Manpower Data Center provided RAND with information from each applicable version for the 11 YATS waves, 1979 NLS, and 1979 AFEES surveys.

The next section discusses our approach in validating FIPS-level ACORN information and compares the enlistment estimates produced by the FIPS and ZIP code approaches. This was a necessary initial step because before this research only ZIP-level ACORN information had been validated, and much of the micro data available to us contained only FIPS code information. Section III describes how we examine the relationship between ACORN information and micro enlistment models and presents our findings concerning the usefulness of the two approaches. In Sec. IV we conclude with the implications of the results and review issues remaining in the segmentation analysis. The Appendix gives the full set of ACORN clusters and related regression results.

II. VALIDATING FIPS-LEVEL ACORN INFORMATION

The ACORN cluster system (see the Appendix) was developed by a private firm, CACI, using the geodemographic characteristics of local neighborhoods. Such marketing categorizations assume that the members of specific subpopulations behave in similar ways in the marketplace because they have similar characteristics and lifestyles. Consistent with this reasoning, significant differences in the enlistment rate have been demonstrated among the clusters. This finding led to the development of ACORN profiles for individual ZIP codes, to help target recruiting literature mailings to specific localities.

We begin by examining the similarity between ZIP code-based ACORN profile estimates of enlistment interest and county-based estimates. This issue was important because the ACORN-enlistment relationship had been validated only for the ZIP code-based ACORN profiles. In certain instances, the individual-level databases at our disposal did not contain ZIP information, having only county of residence for each respondent; thus, before proceeding with the remainder of our research, we needed to verify that the ZIP- and FIPS-based profiles produced similar estimates of enlistment interest.

RESEARCH STEPS

Several steps were required to validate FIPS-level ACORN information. First, ACORN profiles of the U.S. youth population residing in specific counties and ZIP codes of the United States were attached to the YATS respondents' records for the five YATS survey waves containing both Federal Information Processing Standards (FIPS) and ZIP code information by the Defense Manpower Data Center (N = 15,921). These profiles consisted of the proportion of the youth population falling into each of the 44 ACORN geodemographic groups in the particular FIPS or ZIP code within which the respondent resided. Second, we aggregated across respondents to obtain two sets of measures of enlistment interest for each ACORN cluster, first using the FIPS

profile information and then the ZIP profile information; this effort provided a FIPS-based estimate and a ZIP-based estimate of each measure for each cluster.[1] The measures of enlistment interest were the positive propensity rate (the proportion of individuals stating that they are likely to enlist), the production written examination rate (the proportion of persons testing at MEPS or official remote sites to qualify for military service), and the actual enlistment rate. The third step was to assess the similarity of the enlistment interest estimates for the clusters generated by the FIPS versus ZIP approaches and to explore the sources of any differences.[2]

RESULTS

Our analyses showed that the FIPS and ZIP approaches produce similar results, thus validating the FIPS approach. As Table 1 indicates, there was a high Pearson product-moment correlation between the rates estimated for the clusters using the two approaches and a high Spearman correlation of the rank orders of the clusters for each measure of enlistment interest.[3] Given the proposed applications of the ACORN information--for example, to target recruiting literature to areas with greater enlistment interest--the rank order correlations may be the more meaningful statistic and are included for this reason; in any event, the two sets of figures are highly similar.

---

[1]To aggregate individual responses into ACORN-level figures, the enlistment interest scores for a respondent were weighted by the proportion of individuals in his ZIP code (or county) classified into that ACORN and his survey sample weight. The sample weights were designed to reflect national aggregates.

[2]Forty-two of the 44 ACORN clusters were included in this analysis; two of the clusters, each representing fewer than 20 respondents, were omitted due to their small sample sizes.

[3]The Pearson correlation measures the statistical association between the rates estimated for each cluster using the ZIP code and FIPS code profiles. The proportion of variance explained in one rating by the other equals the square of the correlation coefficient. The Spearman correlation measures the association between the rank orders of the clusters based on the rate estimates produced by the ZIP and FIPS profiles.

Table 1

PRODUCT-MOMENT (PEARSON) AND RANK ORDER (SPEARMAN) CORRELATIONS BETWEEN ZIP-BASED AND FIPS-BASED MEASURES OF ENLISTMENT INTEREST

	Correlation	
Enlistment Interest Measure	Product-Moment	Rank Order
Positive propensity rate	.74	.73
Written examination rate	.73	.80
Enlistment rate	.64	.69

NOTE: The results reflect correlations for 42 clusters, based on data from 15,921 YATS respondents. All correlations differ significantly from 0 by t-test ($p < .001$).

The FIPS and ZIP approaches produce similar results; nonetheless, we wanted to examine further the extent and sources of differences in their estimates of enlistment interest. In particular, we wanted to verify that differences in the estimates produced by the two approaches are small relative to the means and standard deviations of the estimates and that there is a logical basis underlying the differences.

To carry out this analysis, we placed the ACORN clusters into four groups, based on the proportion of the population classified in the ACORN and the average ZIP code to FIPS (county) ratio for the cluster (generated from the two ACORN databases). We expected the similarity of the FIPS- and ZIP-based estimates to be greater for ACORNs representing larger proportions of the population and for counties with fewer ZIP codes: ACORNs representing large proportions of the population have smaller YATS sampling distribution errors than those representing small proportions. Less information is lost in aggregating ZIP-based information in counties with few ZIP codes than in more heterogeneous counties. Cutoff points were selected to place an equal number of

clusters in the large (L) versus small (S) population "size" groups and in the large versus small ZIP to FIPS "ratio" groups. The population size cutoff was 2 percent, and the ratio cutoff was 2.32 ZIP codes per county. These limitations resulted in seven ACORN clusters being classified in the LS group, 14 in the LL group, 14 in the SS group, and seven in the SL group; the ACORN groups represent 20, 57, 14, and 9 percent of the population, respectively.

Table 2 shows the average absolute difference in the rate estimates produced by the two approaches for each measure of enlistment interest. Each difference is expressed as a percentage point difference from the corresponding ZIP-based estimate; the means and standard deviations of the ZIP estimates are shown in the last two rows. The analysis indicates that the difference in rate estimates produced by the two

Table 2

SIMILARITY OF ENLISTMENT INTEREST INDICATORS
BY ACORN AND COUNTY SIZE

Size of ACORN	ZIP:FIPS Ratio	% Difference in Propensity Estimates	% Difference in Testing Estimates	% Difference in Enlistment Estimates
L	S	1.7	1.2	0.9
L	L	3.0	1.4	1.0
S	S	4.6	2.3	1.3
S	L	5.6	2.9	2.3
Average rate		35.4	17.7	10.2
(Standard deviation)		(6.9)	(3.7)	(2.4)

NOTE: The numbers represent the absolute difference between estimates generated by FIPS and ZIP approaches for the indicated measure, expressed in percentage points. Average rates and standard deviations of estimates are based on the ZIP approach. The results reflect estimates for 42 clusters--7, 14, 14, and 7 for the LS, LL, SS, and SL groups, respectively--based on data from 15,921 YATS respondents.

approaches is small both in absolute terms and when compared to the means and standard deviations of the estimates. This finding is especially true for large (populous) ACORNs--those containing more than 75 percent of the population. As expected, differences in the estimates tend to increase when the population size of the ACORN is small or when the ACORN population resides in counties containing larger numbers of ZIP codes. The results also suggest that the population size of the ACORN--reflecting limitations of the YATS sample--is more important in producing the observed differences in rate estimates than the ZIP-to-FIPS ratio--reflecting consolidation of ZIP information. In sum, these results together with the correlations reported in the preceding subsection provide considerable support for the use of FIPS-based ACORN profiles.

III. RELATIONSHIP BETWEEN GEODEMOGRAPHIC INFORMATION AND MICRO ENLISTMENT MODELS

Having determined that the FIPS-based enlistment results correspond well with the ZIP code-based ACORN estimates, we now move to the primary topic: the relationship between the information contained in geodemographic databases such as the ACORN and that contained in individual-level models of enlistment decisionmaking. Again, the key question concerns the extent to which enlistment-related characteristics represented in geodemographic databases are already inherent in micro models of enlistment behavior.

Specifically, we address two major issues:

1. Can the micro models be used to predict differences in enlistment rates among geodemographic groups?
2. Does including geodemographic information in the micro models improve the prediction of enlistment decisionmaking?

TASKS IN ASSESSING THE RELATIONSHIP BETWEEN ACORN INFORMATION AND MICRO ENLISTMENT MODELS

Several steps were necessary to assess the relationship between the ACORN information and the YATS-MRS and AFEES-NLS micro models. First, we used each micro model to predict enlistment rates for the ACORN clusters and then determined the correspondence of the predicted rates with the clusters' observed enlisted rates. (The models are discussed in Orvis and Gahart, 1985, 1989; Hosek and Peterson, 1985; Hosek, Peterson, and Eden, 1986. They include background characteristics, economic factors, education, family expectations, military interest, and recruiting factors. (See the Appendix.) The observed enlistment rates for the clusters were determined by aggregating the enlistment information for the respondents in our databases (across counties), according to the respondents' FIPS-based ACORN profiles. Predicted rates were generated using the micro models, based on the characteristics of the individual survey respondents, the regression

coefficients in the micro models, and the FIPS profiles, again aggregating across counties. To the extent that the predicted rates correspond with the observed rates, the implication is that the factors underlying the differences in enlistment rates among the ACORN clusters are captured by the micro models.

Next, we added ACORN information to the vector of variables in each micro model to see how much it improved the prediction of enlistment. Conceptually, this step is related to the analysis just described, because, to the extent the relevant geodemographic information is captured by the micro models, adding the ACORN profiles should have little effect. To carry out this step, several tasks were required. First, we needed to group small ACORN clusters together to form revised ACORN groups/clusters that provided adequate sample sizes for the regression analysis. We grouped together small individual clusters with similar characteristics and enlistment rates within the more broadly defined ACORN groups.[1] Then we regressed the respondent's enlistment decision on the variables in the existing micro model, plus variables from the revised ACORN profile through forward stepwise inclusion. This regression enabled us to identify how many groups/clusters, if any, improved the prediction of enlistment to a statistically significant extent.[2] Third, we investigated the extent of statistical interaction between significant ACORN groups/clusters and the main predictor variables in the micro models. This investigation explored whether one model was appropriate for the various geodemographic groups or whether

[1]The ACORN system consists of 44 individual geodemographic clusters defined within 13 more broadly based geodemographic groups. See the Appendix.

[2]Forward stepwise regression was used because we were interested in whether any of the ACORN groups/clusters would improve the prediction of enlistment to a statistically significant degree when added to the micro model variables. As a practical matter, we note that the finding of only limited statistical significance for the ACORN variables in the stepwise analyses--i.e., the addition of only a few ACORN variables to the models by the procedure--and the minor changes in the coefficients of the other included variables are consistent with the results on the significance of ACORN variables generated by specifications including all the ACORN groups in the micro models. The Appendix presents these specifications.

different models were needed for different groups. Finally, we compared the enlistment decisionmaking predictions made by logistic regression equations generated using the full revised (i.e., grouped) ACORN profiles, the micro model variables, and the vector of variables formed by adding the ACORN profiles to the micro models.

USEFULNESS OF MICRO MODELS IN PREDICTING GEODEMOGRAPHIC VARIATION IN ENLISTMENT

YATS-MRS Models

Our detailed examination of the extent to which micro models explain the variation in enlistment rates among geodemographic groups begins with results from the YATS-MRS database. Using the enlistment information in the database, respondents' county of residence, and the county-based ACORN profiles, observed enlistment rates were determined for each of the ACORN clusters. These rates were compared with a second set of rates. The second set of enlistment rates was predicted based on individual respondents' background characteristics and the regression coefficients in the YATS-MRS micro models for high school students and youths no longer in high school. The FIPS-based profiles and county of residence information were used to allocate both the actual and predicted enlistment rates to the ACORN clusters.

According to our analysis, there is a highly significant correlation ($p < .001$) between the predicted enlistment rates for the ACORN clusters and the observed rates: The YATS-MRS models are very good at explaining enlistment rates among geodemographic groups. For the full sample, including both 18,594 high school students and 18,054 respondents not in high school, the product-moment correlation between the clusters' estimated and observed enlistment rates is .84; the correlation between the rank orders for clusters produced by estimated and observed enlistment rates is .81. Thus, the YATS enlistment models accounted for most of the variation in enlistment rates among the ACORN clusters.[3] (The proportion of variance accounted for equals the square of the correlation coefficient.)

---

[3]The observed enlistment rates vary from .083 to .130; the predicted rates, from .089 to .114. It should be noted that the micro enlistment models were developed using essentially the same databases

AFEES-NLS Models

We undertook an analogous comparison of observed and predicted enlistment rates for the ACORN clusters using the AFEES-NLS enlistment models for high school seniors and recent non-student graduates. This comparison produced results similar to those of the YATS-MRS analysis. Across the full database of 5536 respondents, there was a highly significant correlation ($p < .001$) between the estimated and observed enlistment rates for the ACORN clusters (.73) and an equally high correlation between the rank orders for clusters produced by predicted and observed rates (.76). Once again, the results suggest that the variables in the micro models account for most of the variation in enlistment rates among the geodemographic clusters.*

USEFULNESS OF ADDING GEODEMOGRAPHIC INFORMATION TO MICRO MODELS OF ENLISTMENT BEHAVIOR

The preceding analyses examined the relationship between the ACORN clusters and micro models by exploring the usefulness of the models in predicting differences in enlistment rates among geodemographic groups. We now examine the same issue from the opposite perspective: if adding ACORN information to the micro models improves the prediction of enlistment. The purpose of this analysis is to evaluate the extent to

---

used in this analysis. The YATS-MRS database includes data from 11 administrations of the YATS survey; the micro model was developed with the first 10 waves. Similarly, the AFEES-NLS database is the same one used to develop the enlistment models. Thus, the explanatory power of the individual-level models concerning enlistment behavior differences among ACORN groups/clusters could be reduced to some degree for other YATS/NLS waves.

*Four of the 44 ACORN clusters could not be included in this analysis due to small cell sizes. The somewhat lower correlations obtained for the NLS analysis may result at least in part from the differences between the YATS and NLS enlistment measures. The former apply to enlistment at any time over a period of at least 42 months after the survey and, thus, reflect higher enlistment percentages--particularly for high school students--than the latter, which apply to enlistments near the survey point (spring 1979). This suggests that, statistically, there may be less variance in enlistment behavior to analyze in the NLS database. Indeed, the range in observed rates was .023 to .060; the range in predicted rates was .032 to .066.

which the geodemographic database contains important enlistment-related information not in the micro models. It may be noted at the outset that, given the results presented earlier in this section, we would not expect the geodemographic data to contribute much information.

Results of Stepwise Regressions

Adding information from the ACORN database does little to improve the prediction of enlistment in the micro models. Few ACORN groups or clusters are statistically significant in predicting enlistment, controlling for the factors in the models. Of the 35 groups/clusters formed for possible addition to the YATS-MRS high school model, only five were sufficiently important to be added (i.e., were statistically significant). Only one of 26 was added to the YATS enlistment model for persons no longer in high school. The corresponding figures for AFEES-NLS seniors and graduates were three of 12 and three of 19, respectively. Moreover, for the few ACORN groups that were significant, additional stepwise regressions provided little evidence of interaction with the variables in the micro models. (Only three of 75, four of 20, three of 49, and seven of 54 interaction terms were found to significantly increase the explanatory power of the models. See the Appendix for a discussion of the interaction analyses and results.) As true above, this finding implies that the individual-level models capture most of the enlistment-related information in the geodemographic groupings.

Logistic Regression Results from YATS-MRS Database

Notwithstanding the statistical significance of the several groups/clusters and interactions in the stepwise analyses, our logistic regression results indicate that adding the full (grouped) ACORN profile information for each individual to the micro models has virtually no impact on the distribution of predicted enlistment probabilities. (Regression results and a discussion of the ACORN groups are provided in the Appendix.)

Using the results of logistic regression analyses, three enlistment probabilities were estimated for each respondent. The first was based on his county of residence and the grouped ACORN profile of that county, that is, on ACORN information alone. The second probability was estimated using the individual's background characteristics and the coefficients in the YATS-MRS micro model, that is, on information in the micro model alone. The third probability was estimated by adding the grouped ACORN profile information to the variables in the YATS-MRS micro model.

Each of the three sets of enlistment probabilities was rank ordered across individuals, from lowest predicted enlistment probability to highest, and divided into five groups, i.e., quintiles. The average of the predicted enlistment probabilities within each quintile was then computed. If a model is useful, we should see dispersion of the predicted rates across quintiles. The results for high school students are presented in Table 3. The analysis for respondents not in high school--conducted using a different YATS micro model because of the known differences in factors affecting their enlistment decisionmaking--is presented in Table 4.

The results of the two analyses are similar. ACORN profile information by itself (first column of both tables) was able to account for some of the variation in individuals' enlistment decisions. For example, among high school students, using the ACORN information alone resulted in predicted enlistment rates averaging .10 for the lowest quintile to .16 for the highest quintile. In other words, the quintiles of the sample distinguished by the characteristics in the ACORN profiles had a 60 percent variation in average predicted enlistment rate. However, as seen in the second column, the YATS micro models provided a much better distribution of predicted enlistment rates: they are more powerful models of individual enlistment decisionmaking. Among high school students, for example, the average predicted enlistment rate was only .05 for the lowest quintile, compared to .28 for the highest quintile--a ratio of better than 5:1. In part, this result should be expected because the geodemographic profile information is invariant for

Table 3

PREDICTED ENLISTMENT PROBABILITIES OF YATS RESPONDENTS IN HIGH SCHOOL[a]

Quintile	Average Predicted Enlistment Probability: ACORNs Only	Existing Model	Model Plus ACORNs
1	.10	.05	.05
2	.12	.07	.07
3	.12	.09	.09
4	.14	.14	.14
5	.16	.28	.28

[a]N = 18,594. Actual mean enlistment rate by quintile was .04, .07, .10, .15, and .28.

Table 4

PREDICTED ENLISTMENT PROBABILITIES OF YATS RESPONDENTS NOT IN HIGH SCHOOL[a]

Quintile	Average Predicted Enlistment Probability: ACORNs Only	Existing Model	Model Plus ACORNs
1	.05	.03	.02
2	.06	.04	.04
3	.06	.05	.05
4	.07	.07	.07
5	.08	.14	.14

[a]N = 18,054. Actual mean enlistment rate by quintile was .02, .04, .05, .07, and .14.

all respondents in a given county, whereas their characteristics on the variables in the micro models are free to vary. However, the results in the third column indicate that a more general conclusion is warranted: namely, *enlistment-relevant ACORN profile information is captured in the micro models*. As is quite clear, the addition of the ACORN information to the YATS models had no meaningful impact on the predicted enlistment rates. (Few of the geodemographic groups/clusters had statistically significant effects in improving enlistment prediction when the factors in the individual-level enlistment models are controlled.)

Logistic Regression Results from AFEES-NLS Database

Table 5 and Table 6 show the results of corresponding analyses made for the AFEES-NLS database. As noted earlier, the database is somewhat different from that for the YATS. In this case, we are concerned with

Table 5

PREDICTED ENLISTMENT PROBABILITIES OF NLS HIGH SCHOOL SENIORS[a]

	Average Predicted Enlistment Probability		
Quintile	ACORNs Only	Existing Model	Model Plus ACORNs
1	.02	.00	.00
2	.03	.01	.01
3	.03	.02	.02
4	.04	.04	.04
5	.06	.11	.12

[a]Predicted enlistment probabilities of 408 NLS high school seniors, made from a choice-based regression analysis of 2654 AFEES-NLS respondents. Actual enlistment rates for the NLS respondents are not observed in the choice-based sample.

Table 6

PREDICTED ENLISTMENT PROBABILITIES OF NLS HIGH SCHOOL GRADUATES[a]

	Average Predicted Enlistment Probability		
Quintile	ACORNs Only	Existing Model	Model Plus ACORNs
1	.03	.01	.00
2	.04	.01	.01
3	.05	.02	.02
4	.07	.04	.04
5	.09	.15	.16

[a]Predicted enlistment probabilities of 685 NLS high school graduates, made from a choice-based regression analysis of 2882 AFEES-NLS respondents.

short-term enlistment decisions, and the models are limited to high school seniors and recent graduates not attending school. The micro model variables also differ from those used in the YATS models. Nonetheless, the results of the AFEES-NLS analyses are much the same as those found for the YATS. Use of ACORN profile information alone accounted for some of the variation in enlistment behavior. However, the existing AFEES-NLS enlistment models provided much better dispersion of enlistment rates. Finally, as true for the YATS results, adding ACORN information to the micro models had little impact on the predicted enlistment rates. Again, this finding indicates that the enlistment-relevant geodemographic profile information is captured by the variables in the micro models.

IV. CONCLUSIONS

We conclude by summarizing the implications of our results and highlighting additional findings pertaining to the other market segmentation issues raised in Sec. 1.

IMPLICATIONS OF RESULTS

To reiterate, the findings we have described concerning the YATS-MRS, AFEES-NLS, and ACORN databases suggest that:

- The variables in micro models of enlistment decisionmaking account for most of the differences in enlistment behavior among geodemographic groups.
- Geodemographic groupings add little information to micro models that is meaningful in improving the prediction of individuals' enlistment decisions.
- The same enlistment models can be used for different geodemographic groups.

In short, there is little evidence in our results that geodemographic databases contain significant enlistment-prediction information not already present in individual-level models.

Recall that our goal is to develop models that can be used to forecast enlistment rates for different markets or localities and to help provide guidance on the allocation of recruiting resources. The results presented in this Note are consistent with the notion that geodemographic groupings provide information useful in distinguishing areas with different enlistment rates, and, thus, could be used in such efforts as targeting the mailing of recruiting literature. However, since enlistment decisionmaking micro models appear to capture much of the same information, the research also suggests that the micro models could be used to predict local enlistment rates and provide similar guidance. The general absence of significant interactions between the

ACORN and micro model variables further suggests that the models have wide applicability across geodemographic groups. Differences in enlistment rates among geodemographic groups can be attributed to their differences on variables such as those included in the micro models, not to differences in the process of enlistment decisionmaking.

OTHER ISSUES IN SEGMENTATION ANALYSIS

We conclude the Note by reviewing the other market segmentation issues identified in the Introduction and noting relevant results. One issue concerned whether the factors leading to enlistment vary by stated enlistment propensity. In other words, are the factors that motivate enlistment different among persons who indicate they are unlikely to enlist than among persons indicating they are likely to enlist? This issue is potentially important, given the large proportion of the population stating negative enlistment intentions.

Earlier work (Orvis and Gahart, 1985) and exploratory analyses in conjunction with the modeling of AFQT scores (Orvis and Gahart, 1989) suggest that the factors associated with enlistment in the two propensity groups are similar. Individuals with positive propensity are more likely to have background characteristics associated with enlistment, according to the YATS-MRS and AFEES-NLS micro models; however, the effects of such factors in promoting enlistment appear to be similar for the two groups.

The second issue concerned whether the factors leading to application differ from those leading to enlistment, given that the individual has already applied for military service by taking the written test. This area is important to investigate, given the finding, noted earlier, that approximately half of the applicants do not enlist. Since this group has indicated potential interest in enlisting by taking the test and is already known to recruiters, it is important to understand how the factors that keep people in the enlistment process past the point of taking the written test may differ from those leading up to taking the test. This work will form the subject of a separate RAND report.

APPENDIX
ACORN CLUSTERS AND REGRESSION ANALYSES

The ACORN clustering system of re idential neighborhoods was developed by the private firm CACI. Its purpose is to define a categorization of subpopulations that behave in different ways in the marketplace. The categorization is based on empirical research and the notion that such subpopulations share important characteristics, lifestyles, and values. As a result, we may expect greater homogeneity of behavior within the subpopulations than among them.

The ACORN system consists of 44 individual clusters, which fall into 13 more broadly defined groups. The groups and clusters are listed in Tables A.1 and A.2, together with the number and percentage of 1984 U.S. households they each represent.

Table A.1

ACORN GROUPS

	ACORN Group	Number of 1984 U.S. Households	Percentage of 1984 U.S. Households
A	Wealthy areas	3513266	4.00
B	Upper-middle income, high-value suburbs	16384910	18.67
C	Young, mobile families, multi-unit housing	8789156	10.01
D	High-density rental and condo housing	2537181	2.89
E	Hispanic neighborhoods	6387869	7.28
F	Black neighborhoods	5198671	5.92
G	Middle income family suburbs, blue collar	7196852	8.20
H	Lower-middle, rural, and small town areas	9848586	11.22
I	Older population, lower-middle income	19201119	21.88
J	Mobile homes and seasonal units	1770147	2.02
K	Agricultural areas	857414	0.98
L	Depressed rural towns, blue collar	5584624	6.36
M	Special populations	506517	0.58
	Total	87776312	100.00

Table A.2

ACORN CLUSTERS

	ACORN Cluster	Number of 1984 U.S. Households	Percentage of 1984 U.S. Households
A	1 Wealthy established suburbs	440207	0.50
A	2 Wealthy newer suburbs	900519	1.03
A	3 Wealthy older metro families	2172540	2.48
B	4 Newer high-value suburbs, upper income	2356936	2.69
B	5 High-value post-war suburbs, older families	2290855	2.61
B	6 Mobile young families, high-value suburbs	3021072	3.44
B	7 Older families, high-value newer suburbs	4634854	5.28
B	8 Middle income, older blue collar families	4081193	4.65
C	9 Upper-middle income, high-value condo	1755639	2.00
C	10 Young families, high rent	5144638	5.86
C	11 College undergrads, multi-unit low rent	286227	0.33
C	12 Older college students, multi-unit	1602652	1.83
D	13 Older families, high density, high-rise	1050850	1.20
D	14 Older people, mid-rise, high density	1486331	1.69
E	15 Hispanic lower-middle income	1979170	2.25
E	16 Younger hispanics, Southwestern states	1273399	1.45
E	17 Older population, ethnic mix	1311402	1.49
E	18 Poor ethnic families, very old housing	981386	1.12
E	19 Hispanics and blacks, low rent housing	842512	0.96
F	20 Low-value houses, black neighborhoods	2707736	3.08
F	21 Older black families, old rental housing	1725765	1.97
F	22 Very poor blacks, low rent housing	765170	0.87
G	23 Blue collar middle income families	2978113	3.39
G	24 Blue collar lower-middle, young families	4218739	4.81
H	25 Rural young mobile families	1754939	2.00
H	26 Farms and older housing	1816494	2.07
H	27 Seasonal housing and farms	2829090	3.22
H	28 Rural industrial	3448063	3.93
I	29 Highly mobile older families and retirees	2139487	2.44
I	30 Older families, old metro housing	4644509	5.29
I	31 Older families in small towns	5493335	6.26
I	32 Older Eastern Europeans	934587	1.06
I	33 Rural retirement areas	1802864	2.05
I	34 Older persons, very old, low-value housing	4186337	4.77
J	35 Seasonal housing	728844	0.83
J	36 Mobile home areas	1041303	1.19
K	37 Self-employed farmers	576509	0.66
K	38 Large farms, low-income farm workers	280905	0.32
L	39 Low-income, post-war housing	2734582	3.12
L	40 Rural poor families, high unemployment	78998	0.09
L	41 Rural low-income laborers	2384333	2.72
L	42 Rural large families, very low income	386711	0.44
M	43 Military areas	434825	0.50
M	44 Institutions	71692	0.08
	Total	87776312	100.00

REGRESSION ANALYSES

This portion of the Appendix presents information concerning the regression analyses made to compare the usefulness of geodemographic and micro model information in predicting enlistment. Tables A.3 to A.6 show the variables and coefficients from the logistic regression analyses used to generate predicted enlistment probabilities for the "Model Plus ACORNs" results (see Sec. III), and include the ACORN groupings used for each equation. The ACORN stepwise regressions and interaction term analyses discussed in Sec. III are also described. The YATS-MRS enlistment models are discussed in more detail in Orvis and Gahart (1985, 1989); a detailed description of the AFEES-NLS models can be found in Hosek and Peterson (1985, 1986).

The regression analyses were conducted in the same way for each dataset. First, ACORNs with small sample sizes were consolidated into larger groups based on the ACORN groupings defined by CACI (see Table A.1), the sample sizes of the individual clusters, and the similarity of their enlistment rates. For example, for the YATS-MRS high school student analysis, ACORNs 1 and 2 (wealthy established suburbs and wealthy newer suburbs) were combined because the sample sizes for each were very small and they are members of the same ACORN group (A, wealthy areas). The sample size for ACORN 3 (wealthy older metro families), the other member of group A, was large enough for the cluster to stand alone. In a few cases, the sample sizes for even the combined ACORN groups were so small that it was necessary to drop the ACORNs from the analysis. The resultant ACORN groups/clusters were included with all the micro model variables for the "Model Plus ACORNs" analysis. Table A.3 shows the parameter estimates for the YATS-MRS plus ACORN high school student model; Table A.4 shows the analogous parameter estimates for persons not in high school. The parameter estimates for the AFEES-NLS plus ACORN high school senior model are shown in Table A.5; Table A.6 shows the analogous estimates for high school graduates.

Table A.3

PARAMETER ESTIMATES FOR YATS-MRS HIGH SCHOOL STUDENTS

Factor	Parameter Estimate
Intercept	-1.3920
BACKGROUND CHARACTERISTICS	
Race	
Black	.2632[a]
Other nonwhite	.1723
Region	
East	.1194
North Central	-.0494
West	.0140
ECONOMIC FACTORS	
Perceived ease of finding full-time employment	-.0818[a]
Looking for work	.1184[a]
EDUCATIONAL EXPERIENCE	
Senior	-.1075[a]
Grade-point average	-.0796[a]
Mathematics courses completed	
Geometry	-.1391[a]
Intermediate algebra	-.0410
Trigonometry	-.3120[a]
MILITARY INTEREST	
Intention to enlist	
Very positive	1.8242[a]
Somewhat positive	.8384[a]
Recruiter contact, ever	.2620[a]
Recruiter contact, this year	.1536[a]

Table A.3 (continued)

Factor	Parameter Estimate
ACORN INFORMATION	
ACORNs 1+2	-.0076
ACORN 3	-.0262
ACORN 4	-.0231
ACORN 5	-.0142
ACORN 6	-.0120
ACORN 7	.0067
ACORN 8	-.0017
ACORNs 9+10	-.0034
ACORN 11	-.0067
ACORN 12	-.0039
ACORNs 13+14	-.0217[a]
ACORN 15	-.0099
ACORN 16	-.0085
ACORN 17	.0125
ACORNs 18+19	-.0004
ACORN 20	-.0095
ACORN 21	.0022
ACORN 22	-.0156
ACORN 23	-.0072
ACORN 24	-.0143[a]
ACORN 25	-.0008
ACORN 26	-.0020
ACORN 27	-.0079
ACORN 28	-.0107[a]
ACORN 29	-.0027
ACORNs 30+32	-.0218[a]
ACORN 31	-.0070
ACORN 33	-.0009
ACORN 34	-.0061
ACORNs 35+36	.0040
ACORNs 37+38	-.0059
ACORN 39	-.0062
ACORNs 40+42	-.0021
ACORN 41	-.0084[a]

[a] $p < .05$ (N = 18,594).

Table A.4

PARAMETER ESTIMATES FOR YATS-MRS RESPONDENTS NOT IN HIGH SCHOOL

Factor	Parameter Estimate
Intercept	-2.9213[a]
BACKGROUND CHARACTERISTICS	
Race	
Black	.2776[a]
Other nonwhite	-.0187
Region	
East	.0906
North Central	.0538
West	-.0263
Age	
19 years	-.3540[a]
20 years	-.6908[a]
21 years	-.7375[a]
ECONOMIC FACTORS	
Perceived ease of finding full-time employment	-.0078
Current job status (vs. employed full-time, not in college)	
Employed part-time, not in college	.3514[a]
Looking for work, not in college	.3607[a]
Out of labor force, not in college	.2133
Employed full-time, in college	-.1200
Employed part-time, in college	-.1682
Looking for work, in college	.1345
Out of labor force, in college	-.3331[a]
EDUCATIONAL EXPERIENCE	
Mathematics courses completed in high school	
Intermediate algebra	-.0916

Table A.4 (continued)

Factor	Parameter Estimate
MILITARY INTEREST	
Intention to enlist	
Very positive	1.5697[a]
Somewhat positive	.5530[a]
Recruiter contact, ever	.6084[a]
ACORN INFORMATION	
ACORNs 1+2+3	.0378[a]
ACORN 4	-.0014
ACORN 5	-.0292
ACORN 6	-.0112
ACORN 7	.0070
ACORN 8	.0021
ACORNs 9+10	-.0039
ACORN 11	.0032
ACORN 12	-.0089
ACORN 15	.0014
ACORNs 16+17+18+19	.0016
ACORN 20	-.0095
ACORNs 21+22	.0035
ACORN 23	.0086
ACORN 24	.0019
ACORN 25	-.0045
ACORN 26	-.0076
ACORN 27	.0025
ACORN 28	-.0094
ACORNs 29+33	-.0026
ACORNs 30+32	-.0041
ACORN 31	-.0009
ACORN 34	-.0037
ACORN 39	-.0032
ACORNs 40+41+42	.0028
ACORNs 43+44	-.0014

[a] $p < .05$ (N = 18,054).

Table A.5

PARAMETER ESTIMATES FOR AFEES-NLS HIGH SCHOOL SENIORS

Factor[a]	Parameter Estimate
Intercept	-1.9134
BACKGROUND CHARACTERISTICS	
Race	
Black	.3074
Hispanic	-.0383
Age when senior	
17 years	-.4684[b]
19+ years	.4118
Family situation	
Lives at home	.0757
Family income (in thousands)	-.0261[b]
Mother worked when respondent age 14	.7819[b]
FAMILY EXPECTATIONS	
Plans to never marry	.4382
Plans to marry 6 or more years from survey date	-1.4232[b]
Number of children expected	-.1908[b]
ECONOMIC FACTORS	
Hourly wage, natural log	-.0087
Weekly hours, employed	.0238
Months on job, employed, natural log	-.0305
Not currently employed	-.9397
Weekly hours, not currently employed	-.0124
Months not employed	.3932[b]
Not employed last 12 months	1.0332
EDUCATIONAL EXPERIENCE	
Expects more education	-.2857

Table A.5 (continued)

Factor[a]	Parameter Estimate
RECRUITING FACTORS	
AFQT score	-.0083
AFQT cat. IV (Score 10-30)	-.6782
Share of seniors and recent grads in MEPS (proportion)	-9.4252
Recruiter density in MEPS (per thousand population)	-1286.5627
ACORN INFORMATION	
ACORNs 4+5+6	.0261
ACORN 7	.0240
ACORN 8	.0259
ACORNs 9+11+12	.0669[b]
ACORN 10	.0047
ACORNs 15+16+17+18+19	.0216[b]
ACORNs 20+21+22	.0060
ACORNs 25+26+27+28	.0281[b]
ACORNs 29+30+32+33	.0142
ACORN 31	.0298
ACORN 34	.0523[b]
ACORNs 39+40+41+42	.0179

[a]Regression also includes control variables for wage missing, wage less than $2.25/hour, low family income, and income missing.

[b]$p < .05$ (N = 2654: 408 from NLS, 2246 from AFEES survey).

Table A.6

PARAMETER ESTIMATES FOR AFEES-NLS HIGH SCHOOL GRADUATES

Factor[a]	Parameter Estimate
Intercept	5.8072[b]
BACKGROUND CHARACTERISTICS	
Race	
Black	.9743[b]
Hispanic	-.9519[b]
Age when senior	
17 years	-.1936
19+ years	-.6899[b]
Family Situation	
Lives at home	.0455
Family income (in thousands)	.0047
Mother worked when respondent age 14	.2028
FAMILY EXPECTATIONS	
Currently married	.3264
Plans to never marry	.7652
Plans to marry 6 or more years from survey date	-1.3299[b]
Has children	-.0821
Number of children expected	-.1870[b]
ECONOMIC FACTORS	
Hourly wage, natural log	-.6930[b]
Weekly hours, employed	-.0205[b]
Months on job, employed, natural log	-.1548[b]
Not currently employed	-1.9532[b]
Weekly hours, not currently employed	.0230
Months not employed	.3223[b]
Not employed last 12 months	.2650

Table A.6 (continued)

Factor[a]	Parameter Estimate
EDUCATIONAL EXPERIENCE	
Has GED certificate	-.2976
Expects more education	.6992[b]
Some postsecondary education	-.8629[b]
Months since school, natural log	-.4927[b]
RECRUITING FACTORS	
AFQT score	.0045
AFQT cat. IV (Score 10-30)	.1456
Share of seniors and recent grads in MEPS (proportion)	-39.0982[b]
Recruiter density in MEPS (per thousand population)	352.3309
ACORN INFORMATION	
ACORNs 1+2+3	-.0004
ACORNs 4+5+6	.0474[b]
ACORN 7	.0586[b]
ACORN 8	-.0373[b]
ACORNs 9+11+12	.0046
ACORN 10	-.0407[b]
ACORNs 15+16+17+18+19	-.0018
ACORNs 20	-.0220
ACORNs 21+22	-.0485[b]
ACORN 23	-.0628[b]
ACORN 24	.0116
ACORNs 25+26	-.0039
ACORN 27	.0046
ACORN 28	.0018
ACORNs 29+32+33	-.0053
ACORN 30	.0279
ACORN 31	-.0128
ACORN 34	.0396[b]
ACORNs 39+40+41+42	-.0141

[a]Regression also includes control variables for wage missing, low family income, and income missing.

[b]$p < .05$ (N = 2882: 685 from NLS, 2197 from AFEES survey).

For the forward stepwise regressions predicting enlistment, all of the micro model variables were included, and the same ACORN variables derived from the procedure just described were tested as potential additions to the model. ACORN groups/clusters that significantly added to the variance accounted for by the micro model in the stepwise analysis were interacted with all of the variables in the micro model, and a new stepwise regression analysis was then performed to test the interaction terms as potential additions. In a few cases, interaction terms were colinear with either micro model variables or ACORN main effect terms, and were therefore dropped; most of these had very small sample sizes.

Of the 35 individual ACORNs and ACORN combinations that were entered into the forward stepwise regression analysis for the YATS high school students--along with the 16 variables of the micro model--only 5 significantly added to the predictive power of the micro model (ACORN 4, ACORN 7, ACORNs 30+32, ACORNs 35+36, and ACORNs 43+44). Next, 80 interactions were considered (five ACORN variables x 16 micro model variables). Five of the interaction terms were removed because of colinearity problems, and three of the remaining 75 interaction terms achieved statistical significance in the subsequent forward stepwise regression analysis (ACORN 7 x somewhat positive intention to enlist, ACORNs 30+32 x somewhat positive intention to enlist, and ACORNs 43+44 x very positive intention to enlist).

Of the 26 individual ACORNs and ACORN combinations that were entered into the stepwise regression analysis for YATS respondents not in high school--together with the 20 variables of the micro model--only one significantly added to the predictive power of the micro model (ACORNs 1+2+3). Thus, 20 interactions were considered (one ACORN variable x 20 micro model variables) for the subsequent stepwise regression analysis. Four of the 20 interaction terms achieved statistical significance (ACORNs 1+2+3 x out of labor force, not in college; ACORNs 1+2+3 x employed part-time, in college; ACORNs 1+2+3 x looking for work, in college; and ACORNs 1+2+3 x out of labor force, in college).

Of the 12 individual ACORNs and ACORN combinations that were entered into the stepwise regression along with the 22 variables of the AFEES-NLS high school senior model, only three significantly added to the predictive power of the micro model (ACORNs 9+11+12, ACORNs 25+26+27+28, and ACORN 34). Thus, 66 potential interactions were considered (three ACORN variables x 22 micro model variables). Seventeen of the interaction terms were removed because of colinearity problems, and three of the remaining 49 interaction terms achieved statistical significance in the subsequent stepwise regression analysis (ACORNs 9+11+12 x age 17 when senior, ACORNs 25+26+27+28 x age 17 when senior, and ACORNS 25+26+27+28 x family income).

Of the 19 individual ACORNs and ACORN combinations that were entered into the stepwise regression along with the 27 variables of the AFEES-NLS high school graduate model, only three significantly added to the predictive power of the micro model (ACORNs 21+22, ACORN 23, and ACORNs 39+40+41+42). Thus, 81 potential interactions were considered (three ACORN variables x 27 micro model variables). Twenty-seven of the interaction terms were removed because of colinearity problems, and seven of the remaining 54 interaction terms achieved statistical significance (ACORNs 21+22 x age 17 when senior, ACORNs 21+22 x AFQT cat. IV, ACORN 23 x family income, ACORN 23 x some postsecondary education, ACORN 23 x not employed last 12 months, ACORN 23 x mother worked when respondent age 14, and ACORNs 39+40+41+42 x has GED certificate).

REFERENCES

Berryman, Sue E., Robert M. Bell, and William Lisowski, *The Military Application Process: What Happens In It and Can It Be Improved?*, The RAND Corporation, R-2986-MRAL, May 1983.

CACI, ACORN Market Segmentation System Training Seminars for Defense Manpower Data Center, September 1986.

Hosek, James R., and Christine E. Peterson, *Enlistment Decisions of Young Men*, The RAND Corporation, R-3238-MIL, July 1985.

Hosek, James R., Christine E. Peterson, and Rick Eden, *Educational Expectations and Enlistment Decisions*, The RAND Corporation, R-3350-FMP, March 1986.

Orvis, Bruce R., and Martin T. Gahart, *Relationship of Enlistment Intention and Market Survey Information to Enlistment in Active Duty Military*, The RAND Corporation, N-2292-MIL, June 1985.

Orvis, Bruce R., and Martin T. Gahart, *Quality-Based Analysis Capability for National Youth Surveys: Development, Application, and Implications for Policy*, The RAND Corporation, R-3675-FMP, March 1989.